An Automated Framework of Stress Detection based on EEG Signals

Prashant Lahane, Sushila Palwe
School of Computer Engineering and Technology
Dr. Vishwanath Karad MIT World Peace University
Pune,India
prashant.lahane@mitwpu.edu.in, sushila.palwe@mitwpu.edu.in

Article Info
Page Number: 7101 - 7112
Publication Issue:
Vol 71 No. 4 (2022)

Article History
***Article Received**: 25 March 2022*
***Revised**: 30 April 2022*
***Accepted**: 15 June 2022*
***Publication**: 19 August 2022*

Abstract

Stress is one type of universal emotions faced by everyone. Several factors are responsible for the stress which impact on the low performance of the individual. It also effects on the psychological and physical well being of the person. The more extended period of stress gives depression and suicidal risk. The traditional methods of stress detection were used signals of speech, physiological and facial expression. The traditional methods are less accurate and give problems due to exterior influences such as room temperature, sweating, limb movement, anxiety. A method is required which should be non-invasive, precise, accurate and reliable. EEG signals are the most suitable for stress detection due to its strong correlation with the stress. This paper aims to detect real-time stress based on emotion detection. The EEG signal is acquired using a Neurosky mind wave device, and relevant features are extracted from the time space to the recurrence area using an Alpha Beta frequency Cepstral Coefficient (ABFCC). The separated highlights are characterized into glad as well as angry emotions using classifiers like K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Naive Bayes (NB), decision tree and neural network (NN). Happy and irate feelings are liable for the focused and unstressed condition of the person. As glad emotions are well thought-out a relaxed, and angry emotions are measured as a focused on state. The results show that real-time stress detection using ABFCC and KNN gives the accuracy of 90% for alpha and 92.3% for a beta band which comparatively better than the existing KDE and RER.

Keywords: EEG Signals, Stress Detection, Emotion Recognition.

I. Introduction

Stress is a type of emotion in the field of psychology. The mind of human is imperative body part answerable to different enthusiastic exercises that incorporate stress. Stress could identify utilizing a procedure alike Electroencephalography (EEG), that catches the electrical sign created in the mind. Figure 1. shows the different types of brainwave and table1. represents the EEG bands with a frequency range.

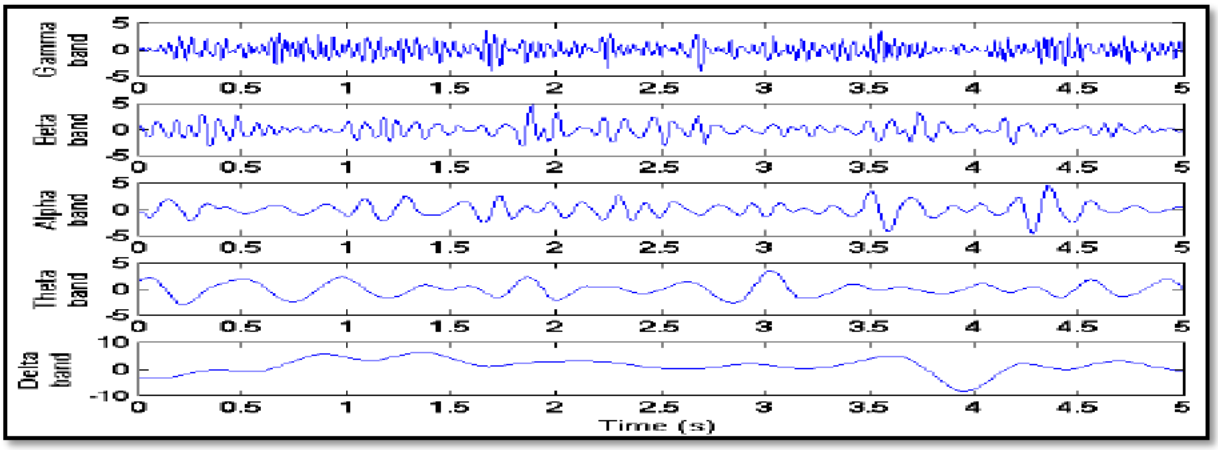

Figure 1: Brainwave: Delta band, Theta band, Alpha band, Beta band, and Gamma band.

EEG Frequency Band Name	Frequency Range
Raw EEG	0-45 Hz
Delta Band	0.5-4 Hz
Theta Band	4-8 Hz
Alpha Band	8-13 Hz
Beta Band	13-32 Hz

Table 1: EEG frequency bands with a frequency range.

In this paper, human emotion analysis based on the EEG signal is performed. EEG signal is acquired using the Neurosky Single channel device by showing videos of Happy and angry emotions as external stimuli to 15 participants.

II. Literature Survey

In the current scenario of a literature survey, several researchers have discovered the ways of EEG signal processing using different feature extraction and classifications techniques. It also presents the classification of emotions from human brain activity. In literature, most of the authors have used different machine learning algorithms to analyse speech signal, face images, EEG signal[2]. Emotion recognition technique using EEG provides a simple, cheap, portable and user-friendly.

EEG-based emotion recognition system consists of emotion elicitation, record subject brain signal, extract band frequency range, feature extraction, feature selection, and features classifications.

Table 2: Literature Survey on Methodologies Used for Stress Detection

Sr. No	Author and year	Physiological Signals	Research Scenario	Accuracy	Observations
1.	Prashant Lahane et.al 2019	Electroencephalography (EEG)	Experimentation are led to exam productivity for highlight taking out utilizing TKE administrator.	87 %	By using EEG detected human emotion and analyzing stress.
2.	Dongkoo Shon et.al 2018	EEG Signals.	Trial for stress examination direct on 17 participants.	68 %	By using the feature selection of genetic algorithm-based detecting enthusiastic stress state.
3.	Khaleel Alhalaseh et.al 2018	EEG	Main stage is interfacing the BlueSmirf to Arduino to alter the baud rate from 11500 to 57600 utilizing an order window.	54%	The utilization of EEG in building based examination.
4.	Neeta Baliram Patil et.al 2017	EEG	Test conduct on a solid individual to show a stress files an incentive before task and after the errand which are intellectual SI and physical SI	60 %	By utilizing EEG. detecting the method of reduction of stress
5.	Sanjeeb Bharali, et.al 2017	EEG	In this analysis they an individual with a significant level of handicap indicate an objective area for their wheelchair.	100%	With the help of home automation and eeg based signals wheelchair which is smart facilities provides for severe patients
6.	Rashima Mahajan et.al . 2017	EEG	Ten subjects (7 females, 3 guys), matured 14 to 18, every one of whom were healthy with no utilization of any medication took an interest trial build the necessary signal dataset of EEG.	70 %	Constant EEG based cognitive brain computer interface for control applications by means of arduino interfacing.
7.	Pandian	EEG	Directed trials on 6 sound	72.66	Constant stress

	Krishnan et.al 2016		subjects who have no history of mental issues or neuro issue.	%	location framework dependent on EEG signals.
8.	Raja Majid Mehmood et.al 2016	EEG pattern recognition.	Analysis was to remove the highlights of different passionate reactions as of subjects of human though assumed graphic enthusiastic boosts. Total photos of 180 which contains 45 photos x 4 states as of similarly conveyed bunches end to end excitement - after database of IAPS.	56.2%	A tale highlight extraction technique dependent twilight optimistic possible feeling acknowledgment of mankind mind sign examples.
9.	VanithaV, Krishnan et.al 2016	EEG	In this directed trials on 6 solid subjects who have no history of mental issues or neuro issue.	72.66 %	Continuous pressure recognition framework dependent on EEG signals.
10.	Chee-Keong et.al 2015	EEG	Students of university “electroencephalography information was gathered span each ninety seconds.	96 %	Investigation in only-conductor electroencephalography uses matlab for association of elicit thru stress of mental.
11.	Narisa N.Y.et.al. 2015	EEG	A plenty of converse critical thinking, and coordinating examinations had apply to multiple signal estimated thru numerous devices set top cover an individual's brain.	93%	The development loose mind wave headsets in the business world
12.	Raja Majid Mehmood et.al 2015	EEG	30 subjects data gathering which (23 to 25) yrs was enrolled for subjects in analysis.	80%	Investigation of frequency wave on network of brain sensors.
13.	Shrutika Lokannavar, et.al 2015	EEG	Power spectral density (PSD) to ascertain highlights of EEG signal.	89%	Feeling acknowledgment utilizing EEG Signals.
14.	Swati N.Moon, et.al 2015	EEG	For this situation the EEG signals were recorded with a Biosemi framework utilizing a top having 32 incorporated terminals.	100%	Determination best topographies aimed at network neural utilizing algorithm of

					genetic and characterization of BCI info.
15.	A. N. Alshbatat et.al 2014	EEG	In this investigation, a constant EEG brain PC outline were projected aimed at regulatory machines. Background includes for the most part EMOTIV EPOIC headphones as well as the module was installed.	100%	EEG-based cerebrum PC interface for robotizing home apparatuses.
16.	Mandeep Singh et.al 2013	EEG	The grouping of neuro physiological information got through EEG on 56 (28 guys and 28 females) volunteers by utilizing pictures chose from the International Affective Picture System, into four enthusiastic states.	Joy - 80%, Fear- 100%, Happiness- 80%.	EEG signal securing, highlights extraction, characterization of feeling and ends from different examinations.
17.	Konstantinos Trochidis et.al 2012	EEG	26 members announced ordinary hearing and no clinical history of neurological malady.	100%	EEG-based feeling recognition during music tuning in.
18.	Kwang Shin Park, et.al 2011	EEG	34 members were involve in the experimentation.	90%	Feeling acknowledgment dependent on the deviated left and right actuation.
19.	L. Zhang et.al 2011	EEG	Five right-gave well being helpers (2 guys, 3 girls females), about aged between 18 to 25 old (unkind = 22.3 and SD = 1.34), took an interest in the investigation.	66.5%	EEG-based emotion recognition using frequency domain features and support vector machines.

Based on the above survey there is a need to have stress evaluation using signal of EEG the stage vibrant part in human life. The signals of EEG use for growing new BCI applications. It is essential for a well set of features which are responsible for stress detection. The accurate stress state measurement is carefully taken into consideration with the different feature extraction and classification techniques. EEG signals give a stronger correlation with stress detection[3]. As per the survey of frontal asymmetry tell us that alpha and beta band ratio of both sides of hemisphere indicate the presence of stress. The EEG signal evaluation for stress level is difficult because of its sensitivity and complexity. Currently, the advance EEG acquisition devices give the signal without the contamination of artifacts such as poor interference, sweating, electrode movement, and other physiological signals. Hence, appropriate physiological parameters can be incorporated into the investigation to broaden the capacity of the basic framework in the measurement of stress state.

III. Methodology

3.1 Data Gathering:

Pre-prepared EEG signals are utilized as contribution of this investigation. For pre-preparing DEAP dataset is utilized to gain the frequencies of range 4.0-45.0 Hz and down examining is performed to 128Hz. A DEAP dataset includes recurrence scope of 4 to 45Hz. In this paper a bandpass channel is utilized and thought about just alpha and beta band frequencies.

3.2 EEG Signal:

The EEG Bands are isolated by utilizing bandpass channel. The bandpass channel is an electronic gadget or circuit that permit the signs between two explicit frequencies to pass, however they victimize the signs at different frequencies. The cut off frequencies f1 and f2 are the frequencies at which the EEG band starts and finishes separately. The worth f2-f1 communicated in the hertz is called channel transmission capacity. The frequencies somewhere in the range of f1 and f2 is known as a channel passband.

$$\mathrm{x(t)} = \{\mathrm{x(t_1)}, \mathrm{x(t_2)}, \mathrm{x(t_{3)}}, ... \mathrm{x(t_n)} \mid 0 < t < n\}$$

$$\text{Band Separations} = \{\text{Delta, Theta, Alpha, Beta, Gamma}\}$$

$$\mathrm{x} = \{\mathrm{x}^{\delta}, \mathrm{x}^{\theta}, \mathrm{x}^{\alpha}, \mathrm{x}^{\beta}, \mathrm{x}^{\gamma}\} \tag{1}$$

3.2 EEG pre-processing

Raw EEG has artifacts and noise that need to be removed from it. EEG is having minimum amplitude and removing the unwanted signal filter are used. To avoid this Neurosky mind wade device gives them without any noise and artifacts in it.

3.3 Feature extraction

The EEG signal acquisition is made using single channel Neurosky Mind wave device. Figure 5 shows the Neurosky single channel mind wave device specifications. The sensor tip to acquire the EEG signal and send using bluetooth connectivity nearby device.

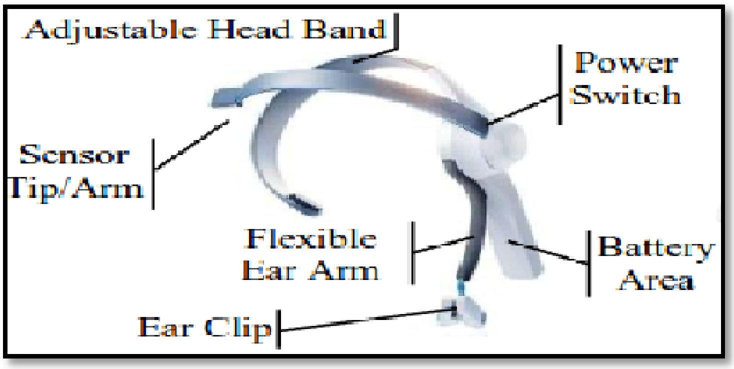

Fig. 5: Neurosky Mind wave Device

This process aims to select relevant features which map EEG into the resulting stress state. An adaptive structure mining method alpha beta rate of recurrence cepstral constant was applied to excerpt relevant structures in the time-frequency domain. It is the relevant approach to extract the frequency of the EEG signal after an interval. The system contains of four phases of information gathering, structure taking out, emotion classification, as well as stress detection. Raw EEG is collected using a wireless device and frequency band are separated. The fundamental highlights are separated, alpha and beta band vitality is determined as an element vector. The extricated highlight is taken care of to various classifiers like SVM, KNN, Bayes, choice tree and neural system for feeling recognition in happy and angry. These feelings are liable for the stressed and unstressed condition of the person. As upbeat feelings are considered as a relaxed state, and furious feelings are considered as a focused-on state. The semantic perspective on the created structure is appeared in Fig. 6.

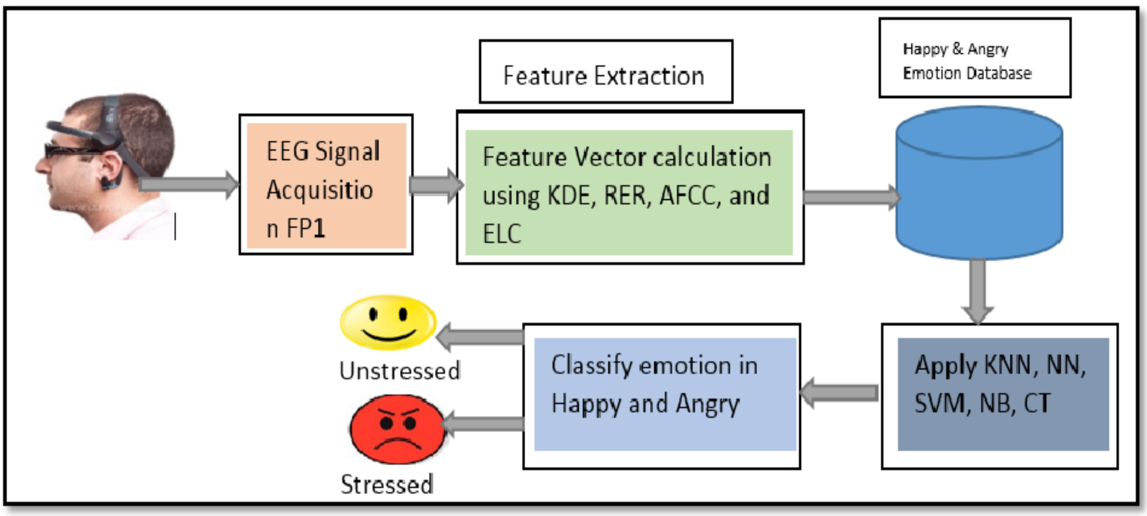

Figure. 6: Schematic view of the real time stress detection system

In this research human stress estimation using the only single-channel device with alpha and beta band is performed accurately. When a person is in stressed the beta band energy is more and when a person is in unstressed, then alpha band energy is more.

3.6 Classification

The characterization is client free which implies information procured from all members are utilized for preparing the classifier. The element vector got through HTT is grouped into impartial or three degrees of (stress-low, stress-medium and stress high).They pick support vector machine (SVM) over different calculations for characterization for two reasons. Initially, it is harsh toward over fitting issue. Besides, its capacity for high speculation and precision with littler preparing test. It is the most vigorous characterization calculation for certifiable situations and effectively applied in numerous issues like face acknowledgment, written by hand character location, interruption recognition and so forth. It is initially planned as paired arrangement calculation, however later it is extemporized to multiclass issues. [20]

IV. Results

4.1 Experimental setup

Results acquired for channel 1 and divert 17 considering the way that these two channels are enough and offer most extreme precision results. It is implemented using Matlab 2018 software, and its results are compared with proposed algorithms. EEG signals were acquired using the Neurosky Mind wave device for the analysis.

4.1 Comparison of different machine learning algorithms on single channel dataset

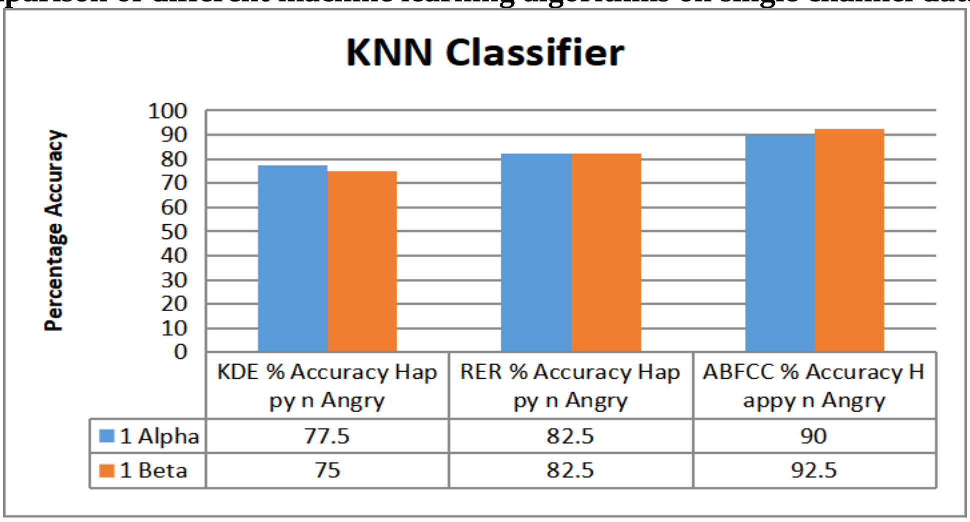

Figure. 4.2: Accuracy Comparison of KDE, RER, ABFCC with KNN classifier

K-Nearest Neighbor (KNN) classifier functions in a simple way by comparing both test and training data based on its nearest value. Where K refers as number of nearest values to be consider before the output is finalized. Implementation of KNN achieved using matlab. The KNN classification accuracy of ABFCC algorithm is 90 for alpha and 92.5 is for the beta band which is comparatively higher than KDE and RER. Values of alpha and beta increasing gradually and show's the progress of anger.

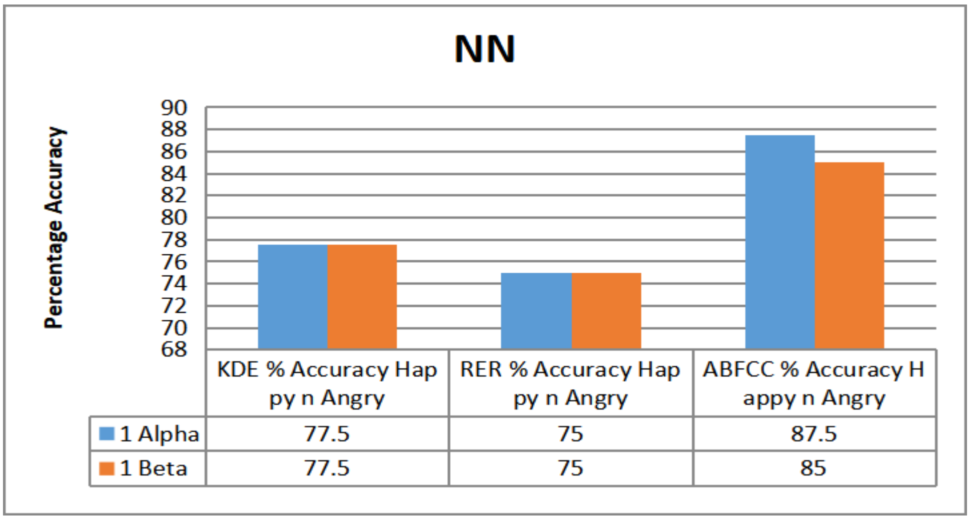

Figure. 4.3: Accuracy Comparison of KDE, RER, ABFCC with NN classifier

Above graph 4.3 shows classification accuracy level of alpha and beta for three feature extration algorithms out of which ABFCC perform better than other algorithms. The neural network classification accuracy alpha band frequency cepstral coefficient (ABFCC) algorithm is 87.5 for alpha and 85 is for the beta band which is comparatively higher than KDE and RER.

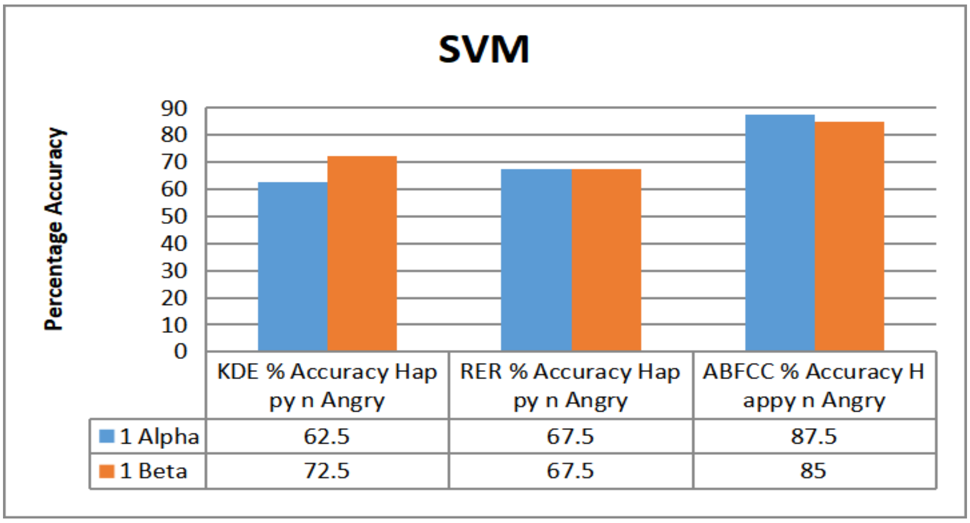

Figure. 4.4: Accuracy comparison of KDE, RER, ABFCC with SVM classifier

The Support vector machine (SVM) classification accuracy of alpha band frequency cepstral coefficient (ABFCC) algorithm is 87.5 for alpha and 85 is for the beta band which is comparatively higher than KDE and RER.

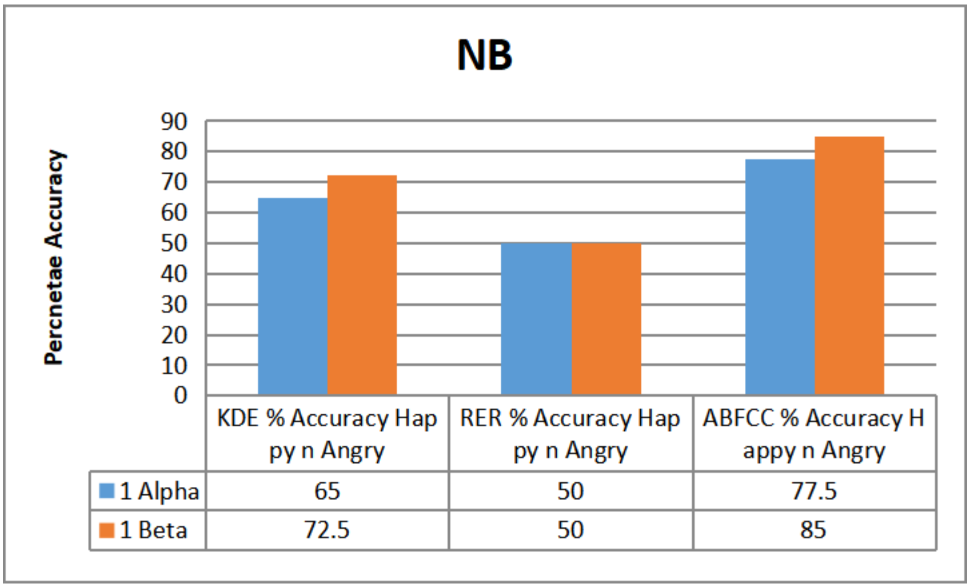

Figure. 4.5: Accuracy Comparison of KDE, RER, ABFCC with NB classifier

Above graph 4.5 shows classification accuracy NB of alpha band frequency cepstral coefficient (ABFCC) algorithm is 77.5 for alpha and 85 is for the beta band which is comparatively higher than KDE and RER.

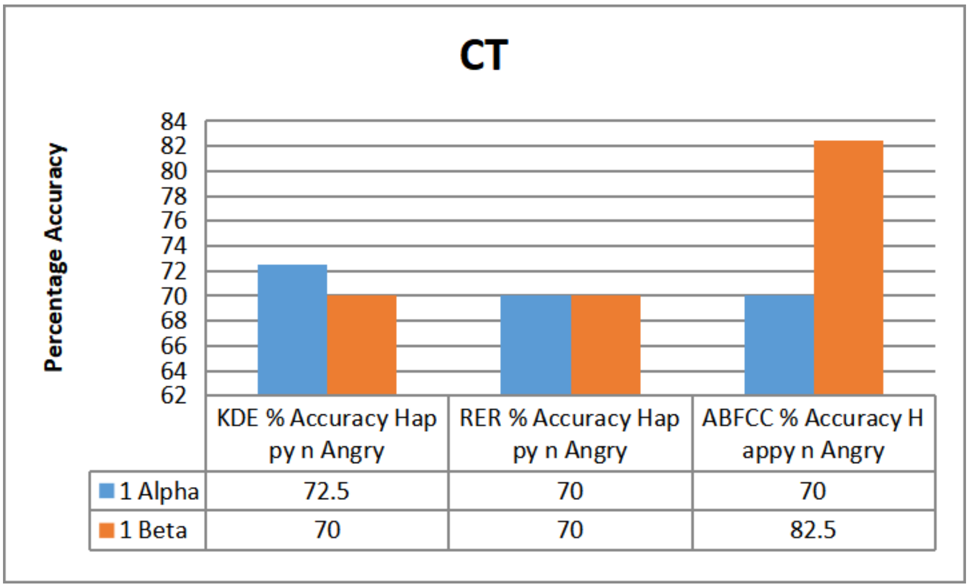

Figure. 4.6: Accuracy Comparison of KDE, RER, ABFCC with CT classifier

Above graph 4.6 shows CT classification accuracy of alpha band frequency cepstral coefficient (ABFCC) algorithm is 70 for alpha and 82.5 is for the beta band which is comparatively higher than KDE and RER.

V. Conclusion

In this paper highlight, extraction and order algorithms were used for human stress level identification based on two basic emotions happy and angry. The analysis of EEG signals and feeling of anxiety is recognized by utilizing just two recurrence groups - alpha and beta as these groups contain generally more stress related data and are additionally adequate to recognize pushed and relaxed individual. The real-time human stress detection system is developed using Neurosky single channel device by creating a database of happy and angry emotions. The novel alpha beta frequency cepstral coefficient feature extraction algorithm is developed. The performance of this algorithm is comparatively better than the existing KDE and RER algorithms.

VI. References

[1] Prashant Lahane and Mythili Trirugnanam, "Research Journal of Pharmaceutical, Biological and Chemical Sciences Literature review of Human Stress analysis using EEG Signal. September – October 2016," vol. 7, no. 2328, pp. 2328–2338.
[2] Prashant Lahane and Mythili Trirugnanam, “Human Emotion Detection and Stress Analysis using EEG Signal,” no. 4, pp. 96–100, 2019.
[3] Prashant Lahane and Mythili Trirugnanam, “EEG-Based stress detection system using human emotions,” vol. 10, pp. 2360–2370, 2018.
[4] “Shocking Statistics of Workplace Stress You Never Knew - Harish Saras.” [Online]. Available: https://www.harishsaras.com/stress-management/shocking-statistics-of-workplace-stress/. [Accessed: 01-Feb-2019].
[5] J. Zhai, A. B. Barreto, C. Chin, and C. Li, “Realization of Stress Detection using Psychophysiological Signals for Improvement of Human-Computer Interactions,” pp. 415–420, 2005.
[6] S. Ito, “A Study on Relationship between Personal Feature of EEG and Human ’ s Characteristic for BCI Based on Mental State,” pp. 4229–4232, 2009.
[7] C. Science, S. A. Hosseini, M. A. Khalilzadeh, and M. B. Naghibi-Sistani, "Emotional Stress States," pp. 60–63, 2010.
[8] A. Saidatul, M. P. Paulraj, S. Yaacob, and N. F. M. Nasir, “Automated System for Stress Evaluation Based on EEG Signal : A Prospective Review,” pp. 167–171, 2011.
[9] N. Sulaiman, S. Armiza, M. Aris, N. Hayatee, and U. T. Mara, “EEG-based Stress Features Using Spectral Centroids Technique and k-Nearest Neighbor Classifier,” 2011.
[10] J. Zhang, W. Wen, F. Huang, and G. Liu, “Recognition of Real-scene Stress in Examination with Heart Rate Features,” pp. 2–5, 2017.
[11] A. E. U, H. N. V, C. G. V, K. C. G, and A. E. Set-up, “Classification of Stress into Emotional, Mental, Physical and No-Stress States Using Electroencephalogram Signal Analysis,” pp. 12–15, 2017.
[12] S. Woo, “Classification of stress and non-stress condition using functional near-infrared spectroscopy,” 2018 18th Int. Conf. Control. Autom. Syst., no. Iccas, pp. 1147–1151, 2018.
[13] A. R. Subhani, W. Mumtaz, M. Naufal, B. I. N. Mohamed, N. Kamel, and A. S. Malik,

"Machine Learning Framework for the Detection of Mental Stress at Multiple Levels," IEEE Access, vol. 5, pp. 13545–13556, 2017.
[14] S. Betti et al., "Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers," vol. 9294, no. c, 2017.
[15] C. Lin, J. King, J. Fan, A. Appaji, and M. Prasad, "The Influence of Acute Stress on Brain Dynamics During Task Switching Activities," pp. 3249–3255, 2018.
[16] C. Viegas and R. Maxion, "Towards Independent Stress Detection : a Dependent Model using Facial Action Units," 2018 Int. Conf. Content-Based Multimedia. Index., pp. 1–6, 2018.
[17] S. Koldijk and M. A. Neerincx, "Detecting work stress in offices by combining unobtrusive sensors," vol. 3045, no. c, 2016.
[18] A. Khorshidtalab, "EEG Signal Classification for Real-Time Brain-Computer Interface Applications : A Review," no. May, pp. 17–19, 2011.
(19) Prashant Lahane, Mythili Thirugnanam, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-4S2 March 2019.
[20] Pandian Krishnan " Real time stress detection system based on EEG signals" 21 December 2016.
[21] Raja Majid Mehmood, Hyo Jong Lee *Computers and Electrical Engineering 53 4 4 4–457, 2016.*
[22] Dongkoo Shon, and Jong-MyonKm Kichang Im,Jeong-Ho Park, Dong-Sun Lim, Byungtae Jang. 5 November 2018.
[23] Ms. Neeta Baliram Patil, Mr. Rahul P. Mirajkar, Ms. Suchita Patil, Ms. Pratibha Patil © 2017, IRJET
[24] Rashima Mahajan, Dipali Bansal "7th International Conference on Advances in Computing & Communications", ICACC 2017, August 22-24, 2017, Cochin, India.
[25] Chee-Keong Alfred Lim and Wai Chong Chia. "*International Journal of Computer Theory and Engineering", Vol. 7, No. 2, April 2015.*
[26] By Narisa N.Y. Chu "IEEE Consumer Electronics magazine" July 2015.
[27] Khaleel Alhalaseh, Hassan Migdadi, Rania Al Halaseh Y, Mohammad Al-Gara. "The IRES International Conference", Antalya, Turkey, January, 2018.
[28] Raja Majid Mehmood and Hyo Jong Lee. Hindi "Publishing Corporation International Journal of Distributed Sensor Networks" Volume 2015, g Lee. Hindi Publishing Corporation International Journal of Distributed Sensor Networks Volume 2015.
[29] RAJA MAJID MEHMOOD RUOYU DU and HYO JONG LEE August 14, 2017.
[30] Shrutika Lokannavar, Prashant Lahane, Apurva Gangurde, Pooja Chidre. "*International Journal of Advanced Research in Computer and Communication Engineering" Vol. 4, Issue 5, May 2015.*
[31] Sanjeeb Bharali, Sharath Chandra, Pooja Dash, Bhushan Chavan. 10 October 2017.
[32] Vanitha V, Krishnan. *Biomedical Research 2016.*
[33] Swati N.Moon, Narendra Bawane, Pratik Hazare. "*International Journal of Advance Research in Computer and Communication Engineering" Vol. 4, Issue 7, July 2015*
[34] A. N. Alshbatat, P. J. Vial, P. Premaratne & L. C. Tran, "EEG-based brain-computer interface for automating home appliances," Journal of Computers, vol. 9, (9) pp. 2159-2166, 2014.
[35] Mandeep Singh, Mooninder Singh, Surabhi Gangwar. IJITKMI Volume 7 • Number 1 • December 2013
[36] Konstantinos Trochidis, Emmanuel Bigand. 12th Instrumentational conference July 2012.
[37] Kwang Shin Park, Hyun Choi, Kuem Ju Lee Jae Yun Lee Kwang Ok An and Eun Ju Kim. International Journal of Medicine and Medical Sciences Vol. 3(6), pp. 201-209, June 2011.
[38] B.-L. Lu, L. Zhang, and J. Kwok (Eds.): ICONIP 2011, Part I, LNCS 7062, pp. 734–743, 2011. Springer-Verlag Berlin Heidelberg 2011.